Short-term water consumption dynamics in El Paso, Texas

Thomas M. Fullerton Jr. and Arturo Elías

Department of Economics and Finance, University of Texas at El Paso, El Paso, Texas, USA

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[1] Time series analysis of water consumption patterns has been the subject of increasing attention in recent years. For many municipalities such efforts offer a means for developing potentially useful planning tools. Because data requirements are not extensive, model development is feasible for markets where information is limited. The work at hand examines the applicability of such a tool in El Paso, Texas, a growing metropolitan economy located in a semiarid region. Sample data are from January 1994 through December 2002. In addition to estimating a linear transfer function equation of water consumption in this city the model is subjected to a series of simulation benchmark tests. *INDEX TERMS:* 6314 Policy Sciences: Demand estimation; 6334 Policy Sciences: Regional planning; 6399 Policy Sciences: General or miscellaneous; *KEYWORDS:* water consumption, transfer function ARIMA analysis, forecast evaluation

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1. Introduction

[2] Water utilities in many areas of the world experience seasonal fluctuations in their aggregate consumption levels. Those fluctuations generally cause specialized maintenance and administrative schedules to be developed for individual utilities as a means of optimizing resources. Such steps also involve specialized supply management procedures in regions where seasonal demands consistently outstrip historical raw water sources. For such areas, accurate forecasts of monthly consumption are of added importance.

[3] Located in a semiarid region, El Paso, Texas, is one such municipality that faces seasonal water constraints. Summer water consumption levels exceed available underground supplies [*Costanzo*, 2004]. In response, water authorities have utilized surface flows of the Rio Grande to provide additional volumes of water beyond what can be extracted from the two aquifers. A mix of conservation efforts have also been utilized for more than a decade to lower per capita demands [*Schmandt*, 2002]. Expanding populations in both El Paso and Ciudad Juárez imply increased consumption levels are still likely to be observed even as usage efficiency improves [*Fullerton and Tinajero*, 2003].

[4] The objective of this paper is to analyze monthly water consumption dynamics in El Paso. It extends earlier water economics research for the borderplex economy [*Fullerton and Schauer*, 2001]. In spite of the seasonal supply constraints described above, short-term water consumption dynamics in El Paso have not previously been modeled. Development of such a tool is potentially useful given the utility infrastructure required to handle seasonal consumption peaks. Model simulations will be employed to verify overall model reliability.

[5] Subsequent sections are as follows. An overview of related literature is provided in the second section. Data and methodology are described in section three. Empirical results are summarized in the fourth section. The final section provides conclusions and suggestions for future research.

2. Literature Review

[6] As a semiarid region that continues to grow, the borderplex economy faces important water limitations [*Ogden-Tamez*, 1996]. Municipal water supply sources for El Paso in 2003 included the Hueco aquifer at approximately 40%, the Mesilla aquifer at roughly 20%, with the remaining 40% coming from the Rio Grande [*Costanzo*, 2004]. All three sources are subject to long-term supply constraints, as well as seasonal fluctuations in both quantity and quality [*Bixby*, 1999]. Concerns over water availability and infrastructure development costs have led to the development of simulation models designed to analyze long-term water consumption trends [*Peach*, 2000; *Fullerton and Schauer*, 2001].

[7] Long-term forecasts are especially helpful for planning, designing, and building future extensions of water systems. Short-term forecasts are used in the operation and management of existing water systems [*Jain et al.*, 2001; *Martínez-Espiñeira*, 2002]. The earlier studies for the borderplex region focus primarily on annual data and do not examine the short-run time series characteristics of urban water demand. Development of monthly and quarterly frequency models should be feasible because they typically do not require extensive data sets [*Hansen and Narayanan*, 1981; *Weber*, 1989].

[8] Because it can incorporate independent regressor variables as arguments, linear transfer function (LTF) analysis is a frequently employed methodology from among the various autoregressive moving average (ARIMA) techniques. *Liu and Lin* [1991] use LTF models to forecast monthly and quarterly residential consumption of natural gas. Similarly, *Tserkezos* [1992] deploys LTF equations to forecast monthly and quarterly residential electricity consumption. In both of those studies, the LTF models consis-

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tently perform well in out-of-sample simulation accuracy exercises.

[9] More recently, *Fullerton and Nava* [2003] estimated an LTF ARIMA model to examine monthly water consumption dynamics in Chihuahua City, Mexico. Variables employed include per meter water consumption levels, rainfall, ambient temperature, average price, and an industrial production index as a business cycle indicator. In addition to parameter estimates that exhibit good statistical traits, the LTF demand model for Chihuahua City also generates out-of-sample forecasts that compare favorably to a random walk benchmark.

[10] The analysis proposed in this paper is similar to that conducted in Chihuahua City by *Fullerton and Nava* [2003]. Because of geographic proximity, El Paso municipal water consumption shares many of the seasonal characteristics associated with Chihuahua City. It also has additional metropolitan business cycle indicators not available for its neighbor to the south. To date, however, the LTF time series methodology has not been tested with respect to the analysis of short-term water consumption patterns in El Paso, other regions of Texas, or other metropolitan economies located along the border with Mexico.

3. Data and Methodology

[11] A fairly good variety of data are available for the investigation of short-term water consumption dynamics in El Paso. They include total municipal water consumed and revenues, weather patterns, plus total nonagricultural employment. Those data can be collected at a monthly frequency from January 1994 through December 2002. Aggregate water consumption, water meter, and revenue (water and sewer) data are reported by El Paso Water Utilities. Weather data for El Paso are recorded by the National Oceanic and Atmospheric Administration. Metropolitan nonagricultural employment and national consumer price index data are collected by the Bureau of Labor Statistics. For local business cycle measurement, the employment series provides the broadest gauge currently available for this city [*Fullerton*, 2001].

[12] Historical data for consumption and tariffs by rate class in El Paso are not presently available [*Fullerton and Schauer*, 2001]. Monthly gallons consumed and the number of meters in use do allow a per customer, or per meter, consumption series to be estimated across all rate categories. Independent variables include average price, employment, and weather measures. To approximate a monthly price series, total water and sewage revenues are divided by total water consumed. The same approach has been used in areas where public utility tariff information is not available or difficult to obtain [*Shin*, 1985]. While providing only an approximation of relevant rates, this approach yields econometric results in line with other measures [*Nieswiadomy and Molina*, 1991; *Dalhuisen et al.*, 2003].

[13] The price variable is deflated using the monthly consumer price index. Because monthly income data do not exist for El Paso, monthly nonagricultural employment is utilized as a proxy for prevailing economic conditions. To measure the impact of weather on water consumption, monthly rainfall in inches, and the number of days with temperatures above 90° Fahrenheit are utilized. Because previous research indicates that outside watering declines during days with rainfall, the number of days with precipitation per month is also included in the sample [*Martínez-Espiñeira*, 2002].

[14] A multiple-input transfer function technique is utilized to study the relationships between water consumption and the independent variables. The LTF method employed is an extension of the traditional Box-Jenkins transfer ARIMA approach [*Box and Jenkins*, 1976]. It highlights the relationships between the dependent variable and the right-hand side variables and involves several steps. Initially, to identify potential lag structures, cross correlation functions (CCFs) are calculated between the stationary component of the dependent variable w and an arbitrary stationary independent variable x with lag k as shown in equation (1):

$$\hat{r}_{xw}(k) = \frac{\sum_{t=1}^{T-k} (x_t - \bar{x})(w_{t+k} - \bar{w})}{\hat{\sigma}_x \hat{\sigma}_w}, \text{ for k} = 0, 1, 2 \ldots, \text{T} \qquad (1)$$

[15] Once an initial transfer lag structure between the dependent and independent variables is identified, the transfer ARIMA equation is estimated. Several rounds of diagnostic checking and reestimation are generally required before selecting the final model [*Box and Jenkins*, 1976]. Under the LTF approach, remaining systematic movements not explained by the independent variables are then modeled using both autoregressive and moving average parameters [*Wei*, 1990].

[16] The general function format for modeling water consumption per customer is summarized in equation (2). Lags for each of the input series, the autoregressive, and moving components are allowed to vary.

$$\begin{aligned} w_t = \theta_0 &+ \sum_{a=1}^{A} a_a p_{t-a} + \sum_{b=1}^{B} b_b emp_{t-b} + \sum_{c=1}^{C} c_c rfi_{t-c} \\ &+ \sum_{d=1}^{D} d_d t90_{t-d} + \sum_{e=1}^{E} e_e rfd_{t-e} + \sum_{i=1}^{p} \phi_i w_{t-i} + \sum_{j=1}^{q} \theta_j u_{t-j} + u_t \end{aligned} \qquad (2)$$

where

- w_t El Paso water consumption per meter in month t, 1000 gallons;
- p_t average real price per 1000 gallons in month t;
- emp_t El Paso nonseasonally adjusted, nonagricultural employment, 1000s;
- rfi_t monthly rainfall in inches;
- $t90_t$ number of days with temperature above 90° Fahrenheit each month;
- rfd_t number of days with rainfall each month.

[17] Hypothesized relationships between the regressors and the dependent variable are the standard ones. Increases in the real price of water should cause reductions in per capita consumption. Improvements in the local economy, proxied here by employment, should cause increases in per capita consumption. Increases in monthly rainfall in inches should lead to reduced consumption, as should increases in the numbers of days per month with measurable rainfall. Finally, hot weather in El Paso, proxied here by the number

of days per month when temperatures exceed 90° Fahrenheit, should cause per capita water consumption to increase.

[18] As a further test of model reliability, several benchmark simulations are used to examine model performance [*McCloskey and Ziliak*, 1996]. That step is taken because good statistical traits do not guarantee out-of-sample simulation accuracy [*Leamer*, 1983]. In addition to the Theil U statistics used to assess model accuracy for Chihuahua City [*Fullerton and Nava*, 2003], a formal, nonparametric test is also applied to the El Paso simulation data [*Diebold and Mariano*, 1995].

[19] Following parameter estimation, a 48-month ex post forecast exercise is conducted. First, a subsample estimation period is defined from January 1994 to December 1998. Model simulation is then conducted for the 12-month period from January 1999 to December 1999. Next, the estimation period is expanded by one month to January 1999 and the forecast period is rolled forward to February 1999 through January 2000. This procedure is conducted 48 times through December 2002. This results in 48 one-month water consumption forecasts, 47 two-month forecasts, 46 three-month forecasts, and so forth to 37 twelve-month forecasts.

[20] In addition, a random walk set of forecasts is compiled using only the latest available historical observation as the prediction for all periods falling beyond the sample range. Benchmark extrapolations compiled in this manner have previously been shown to be accurate relative to econometric and time series counterparts in simulation exercises conducted for regional economies [*Fullerton et al.*, 2001]. The forecasts generated by the LTF model and random walk techniques are then segregated into step length forecasts. The segregated data for both methodologies are then compared to actual El Paso historical water consumption between January 1999 and December 2002.

[21] Using the prediction errors of both methodologies, root mean squared errors (RMSE) are calculated for all 12 simulation step lengths as shown in equation (3).

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{T}}\sum_{\mathrm{t}=1}^{\mathrm{T}}\left(\mathrm{w}_{\mathrm{t}}^{\mathrm{s}} - \mathrm{w}_{\mathrm{t}}^{\mathrm{a}}\right)^2} \qquad (3)$$

In equation (3), w^{s} is the forecast value for w, water consumption per meter. The time index, t, represents the simulation period. w^{a} is the actual value for w. T is the total number of observations for each individual forecast step length.

[22] Theil inequality coefficients are also computed for each of the extrapolation techniques. Also known as U statistics [*Pindyck and Rubinfeld*, 1998], the inequality coefficients are calculated using the formula outlined in equation (4). The denominator in equation (4) causes

$$\mathrm{U} = \frac{\sqrt{\frac{1}{\mathrm{T}}\sum_{\mathrm{t}=1}^{\mathrm{T}}\left(\mathrm{w}_{\mathrm{t}}^{\mathrm{s}} - \mathrm{w}_{\mathrm{t}}^{\mathrm{a}}\right)^2}}{\sqrt{\sum_{\mathrm{t}=1}^{\mathrm{T}}\left(\mathrm{w}_{\mathrm{t}}^{\mathrm{s}}\right)^2} + \sqrt{\sum_{\mathrm{t}=1}^{\mathrm{T}}\left(\mathrm{w}_{\mathrm{t}}^{\mathrm{a}}\right)^2}} \qquad (4)$$

inequality coefficients to vary between 0 and 1. When U = 0, $Y_t^s = Y_t^a$ for all t and a perfect fit is obtained. If U = 1, the predictive performance of the model is as bad as it can possibly be [*Pindyck and Rubinfeld*, 1998].

[23] Information contained in the U statistic can be further analyzed by taking advantage of its three proportions of inequality. The inequality components can be written as shown in equation (5):

$$\begin{aligned} U^M &= \frac{\left(\overline{w}_t^s - \overline{w}_t^a\right)^2}{(1/T)\sum_{t=1}^{T}\left(w_t^s - w_t^a\right)^2}, \\ U^S &= \frac{(\sigma_s - \sigma_a)^2}{(1/T)\sum_{t=1}^{T}\left(w_t^s - w_t^a\right)^2}, \\ U^C &= \frac{2(1-\rho)\sigma_s\sigma_a}{(1/T)\sum_{t=1}^{T}\left(w_t^s - w_t^a\right)^2} \end{aligned} \qquad (5)$$

where $\mathrm{U^M}$, $\mathrm{U^S}$, and $\mathrm{U^C}$ represent bias, variance, and covariance proportions, respectively, of the second moment of the prediction errors [*Theil*, 1961]. The bias proportion measures the extent to which the average values of the simulated and actual series deviate from each other. It thus provides an indication of systematic error. Optimally, the bias proportion will approach zero. The variance proportion indicates the ability of the model to replicate the degree of variability in the variable of interest. Again, as simulation performance improves, the variance proportion approaches zero. The covariance proportion measures unsystematic error. As simulation accuracy improves, the covariance proportion approaches one. The ideal distribution of the inequality proportions over the three sources for any U > 0 is $\mathrm{U^M} = \mathrm{U^S} = 0$ and $\mathrm{U^C} = 1$ [*Theil*, 1961; *Pindyck and Rubinfeld*, 1998].

[24] Modified Theil inequality coefficients are also tabulated for each forecast step length. LTF RMSEs are used in each coefficient numerator and random walk RMSEs in each respective denominator [*Webb*, 1984]. A modified Theil inequality coefficient greater than 1.0 implies that LTF simulations are less accurate than random walk extrapolation for the specific step length. Among others, *West* [1996] indicates that this approach provides reliable rankings of prediction accuracy.

[25] U statistics and modified inequality coefficients are frequently employed in econometric accuracy rankings. Both methods, however, are descriptive and have no statistical significance associated with them. If the difference over time between the RMSEs for the LTF and random walk forecasts is covariance stationary, then another accuracy measure can be utilized. *Diebold and Mariano* [1995] propose a nonparametric t test to examine which extrapolation approach is most accurate. That approach takes the difference between the RMSEs for the random walk and LTF forecasts and regresses them against an intercept term. As shown in equation (6), autoregressive and moving average terms are used to correct for serial correlation.

$$\begin{aligned} (RWrmse_t - LTFrmse_t) &= \theta_0 + V_t, \\ Vt &= \sum_{i=1}^{p}\phi_i V_{t-i} + \sum_{j=1}^{q}\theta_j U_{t-j} + U_t, \\ (RWrmse_t - LTFrmse_t) &= \theta_0 + \sum_{i=1}^{p}\phi_i V_{t-i} + \sum_{j=1}^{q}\theta_j U_{t-j} + U_t, \end{aligned} \qquad (6)$$

Table 1. ARIMA LTF Estimation Results, Water Consumption Per Meter, 1994–2002

Variable	Coefficient	Standard Error	t Statistic	Probability
Constant	−0.0017	0.0625	−0.0270	0.9786
Real Price	−13.0028	1.6553	−7.8554	0.0000
Real Price (−12)	−5.3517	1.6924	−3.1622	0.0022
Employment (−7)	0.1959	0.0561	3.4933	0.0008
Rainfall inches (−1)	−0.5428	0.1429	−3.7971	0.0003
Days above 90	0.1117	0.0160	6.9946	0.0000
Days above 90 (−1)	0.1164	0.0173	6.7216	0.0000
MA(1)	−0.4357	0.0985	−4.4235	0.0000
R^2	0.8848			
Adjusted R^2	0.8755			
Standard error regression	1.0354			
Sum squared residual	93.2726			
Pseudo R^2	0.9912			
Log likelihood	−133.9275			
Durbin−Watson statistic	2.0091			
Mean dependent variable	−0.0228			
Standard deviation dependent variable	2.9347			
Akaike information criterion	2.9879			
Schwarz information criterion	3.2030			
Q statistic (18)	18.5380			
F statistic	95.4447			
Probability (F statistic)	0.0000			

where $RWrmse_t$ is random walk root mean squared error for all 12-month step lengths and $LTFrmse_t$ is LTF root mean squared error for all 12-month step lengths.

4. Empirical Results

[26] All of the raw series are differenced in order to induce stationarity. Estimation output from the LTF modeling procedure appears in Table 1. Coefficient signs for the independent variables are as hypothesized and satisfy the 5% significance criterion. Series lag lengths appear in parentheses.

[27] The constant term in Table 1 is negative. Because the data are differenced prior to estimation, that result reflects a downward trend in water consumption per customer for a period during which conservation programs and higher rates have been employed by the utility [*Costanzo*, 2004]. While the intercept term is not statistically significant, the negative sign makes economic sense [*McCloskey and Ziliak*, 1996] in terms of the gains in usage efficiency observed in recent years in El Paso. The real price variable is included with contemporaneous and 12-month lags. That result is somewhat noteworthy because rate hikes do not show up on consumer bills until after initial month usage has occurred. Inclusion of the contemporaneous lag of the price series points to forward looking expectations behavior on behalf of the customer base in El Paso.

[28] Employment affects water consumption with a lag of 7 months. Rainfall in inches is included with a one-month lag. Days with temperatures above 90° Fahrenheit impacts water consumption with contemporaneous and one-month lags. Lags of the time series data for number of days with rainfall did not exhibit statistical significance and are excluded from the estimation output reported in Table 1. A first-order moving average parameter is included to correct for the effect of serially correlated residuals.

[29] In addition to generally large computed t statistics, the F statistic reported in Table 1 is significant at the 1% level. The low Q statistic generated for the residuals suggests that the equation does not fail to account for any systematic movement in the dependent variable. The coefficient of determination for the dependent variable is high, $R^2 = 0.88$, even though the data have been differenced.

[30] A Pseudo R^2 coefficient is also calculated after transforming the fitted data for the dependent variable back to level form. Once the fitted estimates are in level form, a correlation coefficient is calculated between those data and the actual historical data. Raising the correlation coefficient to the power of two yields the Pseudo R^2 estimate. By that measure, the explanatory power of the model increases to 99% of the variation in the dependent variable over the sample period in question. That result, and the others shown in Table 1, is similar to what is reported for Chihuahua City by *Fullerton and Nava* [2003].

[31] Out-of-sample forecast accuracy for the LTF model is assessed in Table 2. Prediction errors for that technique are used to calculate the RMSE, U statistic, and second moment error proportions for bias (U^m), variance (U^s), and covariance (U^c) values. LTF RMSEs for all 12 step lengths

Table 2. LTF Simulation Accuracy Results, January 1999 to December 2002

Simulations	RMSE	Theil-U	U^m	U^s	U^c
One step ahead	0.9783	0.0267	0.0018	0.0995	0.8987
Two steps ahead	1.0001	0.0268	0.0023	0.1194	0.8783
Three steps ahead	0.9847	0.0265	0.0001	0.1073	0.8926
Four steps ahead	0.9888	0.0264	0.0004	0.1136	0.8860
Five steps ahead	0.9983	0.0265	0.0009	0.1128	0.8863
Six steps ahead	1.0002	0.0266	0.0009	0.1077	0.8914
Seven steps ahead	0.9870	0.0267	0.0043	0.0875	0.9082
Eight steps ahead	0.9883	0.0269	0.0101	0.0700	0.9200
Nine steps ahead	0.9979	0.0043	0.0128	0.0648	0.9224
Ten steps ahead	0.9889	0.0274	0.0059	0.0929	0.9011
Eleven steps ahead	0.9930	0.0275	0.0021	0.1058	0.8921
Twelve steps ahead	1.0069	0.0276	0.0049	0.1198	0.8753

Table 3. Random Walk Simulation Accuracy Results, January 1999 to December 2002

Simulations	RMSE	Theil-U	U^m	U^s	U^c
One step ahead	1.3830	0.0313	0.1213	0.0054	0.8733
Two steps ahead	1.3969	0.0313	0.1272	0.0036	0.8691
Three steps ahead	1.4112	0.0313	0.1339	0.0023	0.8638
Four steps ahead	1.4260	0.0313	0.1407	0.0014	0.8579
Five steps ahead	1.4418	0.0314	0.1417	0.0013	0.8570
Six steps ahead	1.4556	0.0317	0.1530	0.0021	0.8449
Seven steps ahead	1.4726	0.0321	0.1544	0.0029	0.8427
Eight steps ahead	1.3473	0.0311	0.1340	0.0031	0.8629
Nine steps ahead	1.3350	0.0311	0.1194	0.0078	0.8729
Ten steps ahead	1.3341	0.0314	0.1451	0.0022	0.8527
Eleven steps ahead	1.3286	0.0314	0.1312	0.0039	0.8649
Twelve steps ahead	1.3422	0.0315	0.1455	0.0057	0.8488

oscillate near 0.99. That pattern is unexpected because RMSEs usually exhibit incremental growth patterns as forecast periods increase. The bias and variance proportions are low for each of the step lengths. Consequently, the covariance proportion never falls below 87% and the LTF results come close to the optimal distribution of the inequality coefficient proportions. This implies that the transfer function equation forecasts provide good approximations of the systematic movements in El Paso water consumption per meter over time.

[32] The random walk results appearing in Table 3 exhibit empirical traits similar to those of the LTF model. The random walk Theil U statistics are larger than those calculated for the LTF equation. Similarly, the bias and variance proportions of the Theil inequality coefficients are bigger than those obtained for LTF equation, but by relatively small amounts. Random walk prediction error second moment covariance proportions never fall below 84% in Table 3, also a fairly good performance. Table 4 calculates modified Theil coefficients for the two procedures. The modified Theil inequality coefficients are smaller than one for all of the step lengths and oscillate between 0.66 and 0.76. Similar to the earlier results obtained for Chihuahua City [*Fullerton and Nava*, 2003], the RMSEs, Theil U coefficient, second moment inequality bias, variance, and covariance proportions indicate that the simulation performance of the LTF equation for El Paso compares favorably to that of the random walk procedure.

[33] In addition to the descriptive measures discussed above, the *Diebold and Mariano* [1995] non parametric t test is also employed to formally examine whether the predictive accuracies of the sets of forecasts are statistically distinguishable. The estimation output for equation (6) is reported in Table 5. The computed t statistic for the constant term is significant. That result implies that the LTF and random walk RMSEs are statistically different from each other. Because the intercept is greater than zero, it further indicates that the LTF forecasts are more accurate than those of the random walk. The evidence shown in Table 5 provides additional evidence in favor of the LTF modeling approach, but the small number of observations available for the analysis means that it should be treated with caution.

5. Policy Implications

[34] Given the favorable outcomes associated with the estimation and simulation properties of the model, several inferences can be drawn with respect to the conduct of short-term water management policies. Because El Paso experienced a severe drought in 2003, the potential contributions from such modeling tools may be helpful. Given the immediate reaction of per meter consumption levels to price hikes, municipal water authorities may want to consider temporary surcharges above normal rates during unexpected shortages. The model lag structure shown in Table 1 indicates that such a move will lead to an immediate reduction in consumption during the month in which it is enacted and help mitigate the severity of any supply shortfalls.

[35] Decision makers can also utilize prevailing weather patterns in designing short-term policy contingencies. As shown in Table 1, very warm temperatures quickly lead to higher water consumption. To offset that reaction, a temporary surcharge could also be enacted whenever above normal temperatures coincide with below average water supplies. Similarly, rainfall leads to lower consumption levels within 30 days of when it occurs. Extended periods of low precipitation would also therefore be candidates for emergency surcharges.

[36] Results in Table 1 also indicate that water consumption will increase in response to favorable economic conditions. The seven-month lag on the employment variable implies that the reaction time for this process takes longer than what is observed for the other explanatory regressors included in the model. Staff economists at El Paso Water Utilities can take advantage of this by monitoring borderplex business cycle developments [*Fullerton and Tinajero*, 2003]. A booming labor market during a drought could possibly necessitate a relatively high emergency surcharge.

[37] Following protracted negotiations, a new contractual framework has been designed to allow El Paso County farmers sell their rights to irrigation water to the City [*Meritz*, 2004]. The proposed new arrangement, still subject to approval by the United States Bureau of Reclamation, will permit both short-term temporary sales as well as permanent sales of agricultural water rights. All contracts will be transacted at market prices with the initial pilot program expected in 2005.

[38] The flexible design of this proposed arrangement provides the local water utility with a powerful means for addressing periodic shortfalls. Whenever short-range model simulations point to looming supply shortfalls, contingency purchases could be contracted with area farmers [*Michelsen*

Table 4. Modified Theil Inequality Coefficients, January 1999 to December 2002

Simulations	RMSE-LTF	RMSE-RW	Modified U
One step ahead	0.9783	1.3830	0.7074
Two steps ahead	1.0001	1.3969	0.7159
Three steps ahead	0.9847	1.4112	0.6978
Four steps ahead	0.9888	1.4260	0.6934
Five steps ahead	0.9983	1.4418	0.6924
Six steps ahead	1.0002	1.4556	0.6871
Seven steps ahead	0.9870	1.4726	0.6702
Eight steps ahead	0.9883	1.3473	0.7335
Nine steps ahead	0.9979	1.3350	0.7475
Ten steps ahead	0.9889	1.3341	0.7412
Eleven steps ahead	0.9930	1.3286	0.7474
Twelve steps ahead	1.0069	1.3422	0.7502

Table 5. RMSE Arithmetic Difference Model, January 1999 to December 2002

Variable	Coefficient	Standard Error	t Statistic	Probability
Constant	0.3785	0.0543	6.9725	0.0001
AR(1)	0.7361	0.2599	2.8326	0.0196
R^2	0.4713			
Adjusted R^2	0.4126			
Standard error regression	0.0428			
Sum squared residual	0.0165			
Pseudo R^2	NC			
Log likelihood	20.1574			
Durbin-Watson statistic	1.8198			
Mean dependent variable	0.3961			
Standard deviation dependent variable	0.0559			
Akaike information criterion	−3.3014			
Schwarz information criterion	−3.2290			
Q Statistic (18)	3.3001			
F statistic	8.0238			
Probability (F statistic)	0.0196			

and Young, 1993]. The monthly frequency of the model allows seasonal demand extrapolations to be developed throughout the year as new data become available. The appropriate volume of water rights to be purchased can be estimated on the basis of those simulations relative to Bureau of Reclamation regional reservoir forecasts [*Cortez*, 2001]. The level of the market price prevailing whenever a contingency purchase is made will also affect the size of related temporary surcharges that would potentially be used to pay for the supply increments.

[39] Capital outlay and maintenance programs are forcing permanent rate increases to be instituted by El Paso Water Utilities. Those increases are scheduled to be phased in over a period of several years [*Crowder*, 2002]. Once the increases occur, they will lead to per meter consumption declines. Simulations with this type of dynamic model can provide insights with respect to the timing and size of those reactions to the price hikes. While the rate increases are scheduled several years in advance, prevailing economic and weather conditions will affect short-run customer behavior in manners that cannot be anticipated without additional analysis.

6. Conclusion

[40] In this study, an ARIMA Linear Transfer Function model is estimated to study short-term water consumption dynamics in El Paso. The data used are monthly time series of per-meter water consumption, days with temperature above 90° Fahrenheit, rainfall in inches, number of days with rainfall, average real price, and nonagricultural employment (as a proxy for income). Results obtained are quantitatively similar to those obtained for another metropolitan economy using the LTF methodology. Monthly water consumption reacts fairly quickly to changes in both economic and climatic variables. All of the estimated coefficients exhibit the hypothesized algebraic signs.

[41] Simulations generated using the LTF model are also compared to a random walk benchmark for testing out-of-sample forecast accuracy. A 48-month ex post forecast exercise was conducted and sorted into one through twelve step-length sets. Modified Theil inequality coefficients indicate that the LTF produces superior monthly water consumption projections for all 12 step lengths. The random walk RMSE estimates are larger than those of the LTF RMSEs. In addition, a nonparametric test is used to examine whether the LTF accuracy improvement is statistically significant. The last test also provides evidence in favor of the LTF modeling approach.

[42] Although many of the estimation results confirm conventional wisdom regarding water demand, the nature of the lag structures cannot be known without empirical testing. Results of such exercises carry potentially important policy implications. Similarly, temporary pricing and purchasing policies can benefit from having access to market-specific models such as the one detailed herein. Simulation accuracy performance is also important for policy makers who anticipate utilizing tools such as econometric models in rate design.

[43] Because it has been applied to relatively few regional markets, it would be helpful to replicate this effort for other metropolitan economies. Monthly rate and income data are generally difficult to obtain, but can be partially overcome using average price and employment series as proxies. If feasible, the monthly water consumption analysis of single-family, multifamily, commercial, and industrial customer categories might provide additional information beyond that of the aggregate per customer approach adopted herein. Capital costs and supply constraints make it likely that utility managers will require accurate demand forecasts as one ingredient for better operations planning.

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A. Elías and T. M. Fullerton Jr., Department of Economics and Finance, University of Texas at El Paso, El Paso, Texas, USA. (arturo_elias@yahoo.com; tomf@utep.edu)